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Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects

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ABSTRACT

In a large number of energy models, the use of learning curves for estimating technological improvements has become popular. This is based on the assumption that technological development can be monitored by following cost development as a function of market size. However, recent data show that in some stages of photovoltaic technology (PV) production, the market price of PV modules stabilizes even though the cumulative capacity increases. This implies that no technological improvement takes place in these periods: the cost predicted by the learning curve in the PV study is lower than the market one. We propose that this bias results from ignoring the effects of input prices and scale effects, and that incorporating the input prices and scale effects into the learning curve theory is an important issue in making cost predictions more reliable. In this paper, a methodology is described to incorporate the scale and input-prices effect as the additional variables into the one factor learning curve, which leads to the definition of the multi-factor learning curve. This multi-factor learning curve is not only derived from economic theories, but also supported by an empirical study. The results clearly show that input prices and scale effects are to be included, and that, although market prices are stabilizing, learning is still taking place.

Contents

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1. Introduction

Many governments in the world adopt strict energy policies to reduce their fossil fuel consumption and decrease the greenhouse-gas (GHG) emission level as to contribute to alleviating the global warming problem. They provide economic incentives and increase R&D budgets to promote renewable energies. In order to forecast future global warming trends and GHG emission levels, experts build up energy-environment-economy models to simulate those impacts. These models, however, are extremely sensitive to the assumptions about the improvement and deployment of new technologies [1]. Technological change is commonly regarded as the most important factor to estimate the trends of these new technologies. Thus, the technological learning concept recently has been widely applied in these models, and plays a key role in the simulation processes incorporated within these models [2].

Generally, technological learning concepts are simulated through the learning curve model, which explains the relationship between cost decrease and output growth [3]. The learning curve model is based on the observed fact that as experience with a technology accumulates, as represented by cumulative production, the performance of that technology, in terms of unit production cost, improves [2]. The learning curve allows for the estimation of a decrease in unit production costs as a result of an increase in cumulative production. Explanations supporting learning curve theory identify various types of learning, i.e., learning-by-doing, learning-by-researching, learning-by-using and learning-by-interacting. The Boston Consulting Group [4] mentions that "increasing accumulated experience in the early stages of a technology is a dominant strategy for both maximizing the profitability of firms and the social benefits of technology-related public policy". As an important implication of the learning curve, Grübler et al. [5] point out that it is an essential bridge between innovation and integrated assessment of climate change. It is clear that the learning curve plays an important role in designing effective energy policies, being a vital approach for simulating technical changes.

The learning curve describes the costs of a given technology being changed through one factor, which is represented by cumulative capacity or production of a certain technology [2,6]. It illustrates that when a new technology is brought in the market, the cost per unit is initially high, but as cumulative output increases, the cost per unit decreases in an orderly way [7]. This type of learning curve is the so-called one-factor learning curve (OFLC). The usual form to express the OFLC is by using a power function [8]:

$$C = C_i Q^{-b} \tag{1}$$

where C is the cost per unit of production, installed capacity or capital, C_i is the cost of the first unit installed or produced, Q is the cumulative capacity or output, b is the learning index or experience index. The time step usually employed is 1 year, with C and Q being determined every year. By taking the logarithm on both sides, a linear equation is obtained:

$$\log C = \log C_i - b \log Q + \varepsilon \tag{2}$$

in which ε represents a residual term. This term ε is added to a regression equation in order to introduce all of the variation in cost that cannot be explained by included independent variables ($\log C_i$, $b \log Q$) [9]. The so-called progress rate and learning rate can be determined from Eq. (1) as follows:

$$\text{Progress rate}: \quad Pr = 2^{-b}, \quad \text{learning rate}: \quad \mathrm{Lr} = 1 - 2^{-b} \tag{3}$$

These two equations are always used to express the percent changes in cost as a result of doubling of cumulative capacity. For example, a learning rate of 20% shows that after doubling of cumulative capacity, the costs are decreased to 80% of their initial level.

The OFLC, however, only describes the relationship between cost changes and cumulative capacity. There is a problem of omitted variable bias. Econometric theory argues that if an independent variable, whose regression coefficient is nonzero, is excluded from the model, the estimated values of all the regression coefficients will be biased unless the excluded variable is uncorrelated with other variables [9,10]. For example, if we only use the OFLC ($\log C = \log C_i - b\log Q + \varepsilon$) to represent the learning effects and ignore the independent variable learning-by-researching (KS) whose regression coefficient ε is nonzero, the total residual term ε will be $\varepsilon + \alpha \log KS$, with α the elasticity of learning-by-researching or knowledge stock index. Thus, as also Nemet [6] indicated, the cumulative capacity is not the unique factor that determines the cost changes.

Since the OFLC ignores the effects of cumulative R&D expenditures, incorporating the effects of knowledge acquired from other sources, such as R&D or other industries, becomes an essential issue. Recently, the OFLC has been extended by integrating the knowledge stock (KS) as an additional variable [11–13]:

$$C = C_i Q^{-b} KS^{-\alpha}; \quad \log C = \log C_i - b \log Q - \alpha \log KS + \varepsilon \tag{4}$$

in which KS is defined as $KS_t = (1 - \eta)KS_{t-1} + RD_t$, η is the annual depreciation rate, RD_t represents R&D expenditures at time t, and α is the elasticity of learning-by-researching or knowledge stock index. This extended equation is commonly denoted as the two-factor learning curve (TFLC). The concept of the TFLC clearly identifies knowledge stock as a variable of technological learning. It explains that cost reduction occurs as resulting from learning-by-doing and learning-by-researching combined [2].

Fig. 1 shows schematically the interactions between R&D and production growth through learning-by-researching and learning-by-doing leading to cost reduction. It depicts the direct and

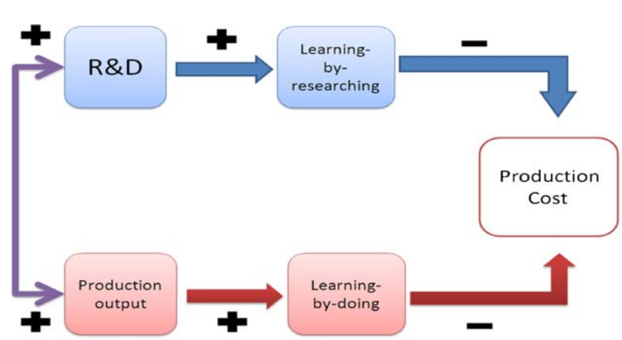

Fig. 1. Relationships and feedbacks between R&D, production growth and production cost.

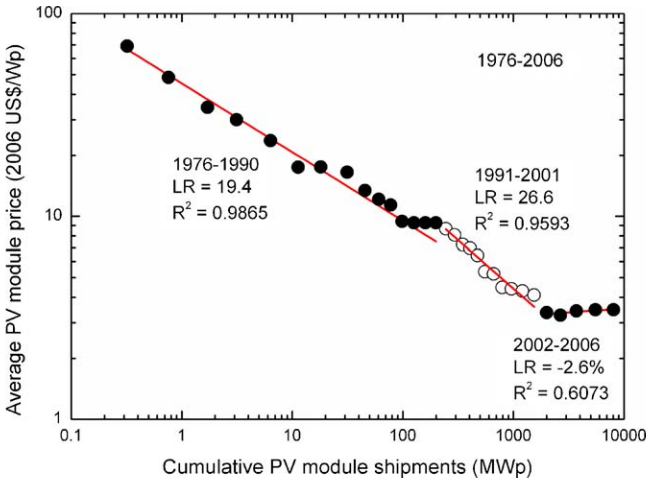

Fig. 2. The PV learning curve in various time periods: 1976–1990, 1991–2001 and 2002–2006.*Source*: 1976–2001 [57]; 2002–2006 [19].

indirect relationship between learning-by-doing and learning-by-researching. With an increase of R&D investment, learning-by-researching will be enhanced, which leads to falling cost directly. An increase of R&D investment meanwhile improves the production process, which enhances learning-by-doing as well. On the other hand, the growth of output increases learning-by-doing, which results in cost reduction directly. It supports, in the meantime, the R&D investment that improves learning-by-researching. The interactions of these factors finally lead to cost reduction of a new technology.

Over the past decades a considerable number of studies have been carried out on learning curve analysis, especially in emerging energy technologies, e.g. [14–17], however, it must be noted that many questions still remain unsolved. First of all, the learning curve is not a theory, but an empirical research method, although recently Wene [18] has developed a theoretical approach based on cybernetic concepts. It cannot tackle or explain discontinuity issues and ignores (changes in) data quality. The distributions of the learning rates vary among different energy technologies; even some negative estimations have been found; a recent update is provided by Junginger et al. [3]. This variability is not only observed among the different technologies, but also among the same type of energy technologies. Recently, some studies pointed out that the uncertainties in key parameters might be significant [19,20]. Fig. 2 shows the learning rate of PV for the period of 1976–1990 is determined to be 19.4%, while for the period of 1991–2001, it is determined to be 26.6%. Parente et al. [21] and Van Sark [22] use the same time period data, but obtain different learning rates for PV production as evidenced in Table 1: it is clear that all these evidence illustrates one issue: the learning rate is not constant.

One cause of these observed changes in learning rates is that mostly not production data are used but market prices. Market prices do not always follow production cost, for various reasons. They may be higher and sometimes also lower than production cost. For example, shortages in production capacity will drive up price while the production cost will remain unchanged or will even decrease. Therefore changes in the market price will only reflect production cost if they are viewed on time scales of 5 years and more. Temporary market effects on price are likely to be an important reason behind the discontinuity in the PV learning after 2002 when the PV industry had problems to keep abreast with the rapidly expanding German market.

Schrattenholzer [23] argues that variations in learning rates are being caused by using different data sets, time spans and performance measures, and that experience depreciation is the main reason behind negative learning rates, such as shown in Fig. 2 for the period 2002–2006. Jamasb [13] considers that the variability can be explained by the stage of technological development or the technology life cycle. Van Sark [22] indicates that when the first unit cost, the data span, the inflation and the exchange rate are changed, the learning rate will be altered as well. It implies that small changes in the learning rate lead to large differences in forecasting technology development. Clearly, and also according to Wene [15] and Neij et al. [24], the learning curve may not be an appropriate way to estimate the cost of some technologies.

Aside from the discontinuity issue, as illustrated in Fig. 2, Hall and Howell [7] indicate that the learning curve might become flat over a short period. Swanson [19] indeed observes that the cost trend of PV has been flat in recent years, even though the cumulative capacity increases. Moreover, Fig. 2 shows that the learning rate for the period of 2002–2006 is even negative: −2.6%. This flatted or blunted learning curve represents that apparently no learning effect is taking place during this short period. This situation is namely "learning without doing" [25]. Pan and Köhler [26] conclude that the learning curve may successfully describe the cost reduction of a given technology at its emerging stage, but fails to explain the cost changes at its mature stage.

Swanson [19] and Nemet [27] further suggest that a much broader set of influences than experience alone is accounting for the rapid cost reduction. The Boston Consulting Group [4] does not purely refer to the relationship between labor productivity and cumulative output in its report. It argues that there are several reasons related to the cost reduction: learning effects, scale effects, cost rationalization and technology improvement [4]. Hall and Howell [7] consider that the sources of falling cost may include: economies of scale, technological progress, input price changes, internal efficiency and learning-by-doing. Of these factors, the economies of scale may play an important role in cost reduction. Cory et al. [28] and Ibenholt [29] also assert that cumulative capacity is not the only element determining cost; other factors such as R&D, economies of scale, input prices can change the costs as well. Isoard and Soria [30] decompose the cost into a learning and scale effect. They observe that learning effects are over-estimated when the scale effect is not taken into account. Moreover, Söderholm and Sundqvist [31] conclude that the role of input prices has to be assessed in order to realize whether the input prices change the cost over a time period. It is important to note that the costs of a technology are changed by variables other than cumulative capacity alone, perhaps most remarkably by input prices and economies of scale [2,26,31]. Nemet [27] adopted an alternative approach based on a traditional engineering analysis to analyze technological change. Instead of cumulative output alone, he decomposes the module cost of PV production into several factors: raw material, plant and wafer size, average module cost, and module efficiency, leading to a function F in which all these factors are introduced as variables:

$$\Delta Cost_t = \Delta Cost_{t-1} \cdot F(\eta,\ size,\ yield,\ poly,\ sicost,\ siconsum,\ wafer)$$

in which $\Delta Cost_t$ and $\Delta Cost_{t-1}$ is the total change in module cost at time t and $t-1$, η is the module efficiency, *size* represents the plant size, *yield* is the proportion of functioning units available at the end

Table 1
Learning rates for PV technology development for different periods.

	1981–1990	1991–2000	1981–2000
Parente et al. [21]	0.2	0.22	0.23
Van Sark [22]	0.16	0.29	0.18

of the manufacturing process, *poly* represents the poly-crystalline share, *sicost* represents the silicon cost, *siconsum* is the silicon consumption, and *wafer* is the wafer size. The results of his model show that these factors fail to explain most of the changes over the period of 1975–1979, as 59% of the change is unexplained. It is clear that his approach cannot give us a whole picture about scale effects, input prices, and learning effects.

Apparently all these studies confirm one thing that incorporating the scale and input-prices effect at this moment is an inevitable task. This paper therefore attempts to develop and validate a multi-factor learning curve (MFLC), using PV technology development as case. Having identified causes for cost reductions, a more accurate forecast of future PV prices may be possible, using forecast of e.g. input price development. We will demonstrate this as well.

This paper is organized as follows. The characteristics of and differences between learning, scale and input-prices effect are outlined briefly in Section 2. The methodology is described in Section 3, in which two economic theories related to this study are introduced. In Section 4, the input identification and the boundaries of this study are discussed. A new modular model is built up to express these various effects. In Section 5, the results of the MFLC model compared with the OFLC model are depicted for the case of PV technology development by dividing the analysis time period into three parts. In Section 6, two scenarios are used to forecast the future prices of PV modules. Finally, conclusions are presented in Section 7.

2. The effect of scale, learning and input prices

It will be useful to make a distinction between two kinds of effects: learning and scale. In economics terms, the scale effect can be described either as economies of scale or returns-to-scale. Most learning curve studies only discuss the economies of scale and ignore its counterpart: the diseconomies of scale [2,7,26,31]. Economies of scale describe that the output of a given product can be doubled for less than a doubling of cost; diseconomies of scale describe a doubling of output requiring more than a doubling of cost. Returns-to-scale is the rate at which output increases as inputs are increased proportionally. It is always divided into three phases: increasing, constant and decreasing returns-to-scale. The input prices affect the production cost depending on the development of input prices. All these factors are discussed in the following subsections.

2.1. Economies of scale, diseconomies of scale and returns-to-scale

In the last few decades, several papers have been devoted to the study of the scale effect in PV technology, but the results vary among these researches. The scale effect can be measured as $(Size_t/Size_{t-1})^{\phi}$ where size represents the plant size, t represents time (year) and φ represents the scaling factor [27]. The range of scaling factors, as found in the literature, is shown in Table 2, and is between −0.07 and −0.20. These numbers are obtained without considering the learning, scale and input prices effects. Such large variation results from differences in the time period, data source, methodology, and purpose.

Economies of scale can be measured by a cost-output elasticity, which is defined as the marginal cost being divided by average cost [32]. If marginal cost is less than average cost, this is denoted as economies of scale. The effects of economies of scale eventually bring about a decreasing average unit cost as the output increases [2,30]. Returns-to-scale is used as an alternative to describe the scale effect. In terms of returns-to-scale, an increase of returns-to-scale implies that output more than doubles when inputs are doubled. It results from the larger scale of a production plant allowing managers and workers to have a larger specialization in their tasks. The complicated and large-scale equipment meanwhile can be operated more effectively to increase productivity [33].

Table 2
The various scaling factors in PV technology between 1997 and 2003.

Scaling factor	Reference
−0.18	Gruber [54]
−0.07	Bruton and Woodock [47]
−0.20	Ghannam et al. [55]
−0.12	Frantzis et al. [56]
−0.09	Rohatgi [48]

On the long run, a firm might change its input proportions as the level of output changes. If the firm continues to grow, it may suffer from the diseconomies of scale due to having difficulty in management [33]. The marginal cost of diseconomies of scale is larger than average cost [32]. Diseconomies of scale can be described by decreasing returns-to-scale, which illustrates that output is less than doubled when all inputs are doubled with large-scale operation. It arises from the difficulties in organizing and running a large-scale operation, so that it leads to decreases of efficiency and productivity [33]. Finally, the diseconomies of scale in the meantime take place instead of economies of scale. However, there is a special case. When cost increases proportionally with output, it is neither economies nor diseconomies of scale [32]. It is commonly regarded as the constant returns-to-scale, which explains that output doubles when all inputs are doubled.

2.2. Learning effects

As discussed above, it may be tempting to conclude that with the economies of scale (increasing returns-to-scale), firms can achieve their aim of cost reduction, but this need not be true. In fact, the average cost of a new technology is relatively high at an initial low level of output. At this stage, no economies of scale take place. With learning, the cost of production for a firm can be reduced regardless of the plant size [32]. Learning effects include learning-by-doing, learning-by-researching, learning-by interacting, and learning-by-using [3]. Of these effects, we mainly describe the following learning effects as the others are not considered important here:

- *Learning-by-doing*: Workers often take longer time to finish a given task at the first few times they perform that task. As they repeat doing the same task many times, their speed (or efficiency) increases. Eventually, it improves the production processes and accumulates the experience of the workers. Managers learn to plan the production process more effectively through the organization of the flow of all inputs. All this can be described by learning-by-doing, and it always takes place at the production stage. When managers and laborers gain experience with production, it leads to cost reduction due to learning-by-doing [2,32,33].
- *Learning-by-researching*: Increasing research investments improve the innovation process. As a result, many specialized tools are introduced into the design and production processes. Learning-by-researching does not only take place at the invention stage, but also can be observed at the diffusion and saturation stages of a technology [2].
- *Learning-by-interacting*: The interactions between the various stakeholders, such as the suppliers of materials, transportation, end-users and policy makers, enhance the diffusion of knowledge. This can be called learning-by-interacting. It always takes place at the large diffusion stage [5].

2.3. Scale effects versus learning effects

In Fig. 3 scale effects and learning effects are compared schematically. Here, AC_1 represents the long-run average unit cost curve. The economies of scale effects occur along the unit cost curve, AC_1. Due to economies of scale, the change in production

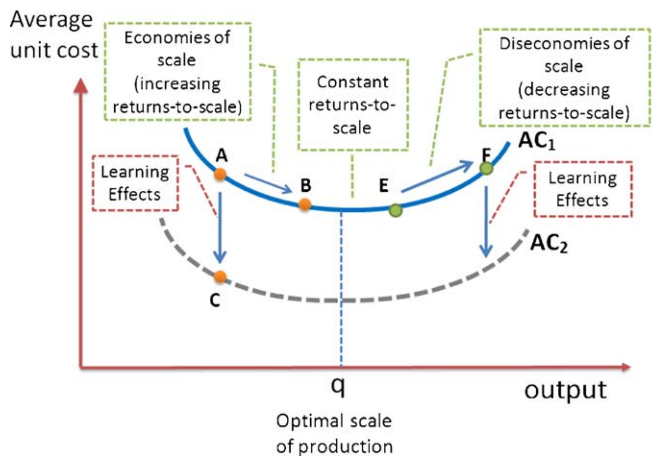

Fig. 3. Scale effects versus learning effects.

from A to B along AC_1 leads to lower cost. As a firm continues to enlarge its plant size, an optimal scale of production eventually is reached. At this stage, constant returns-to-scale takes place [30]. However, when the size of the plant is expanded further, the change in production from E to F along AC_1 leads to higher cost due to diseconomies of scale. In contrast to scale effects, the learning effect shifts the whole average cost curve downward, from AC_1 to AC_2. The move from A on AC_1 to C on AC_2 leads to lower cost due to learning effects regardless of the current scale of production [30,32]. Furthermore, an optimal scale of production q may exist between the economies and diseconomies of scale. It is clear that economies of scale or returns-to-scale are a short-term effect, while learning is a long-term effect [30,30].

2.4. Input prices

In general, inputs can be grouped into three categories: capital (K), labor (L) and materials (M) (oil, water, copper, etc.). All firms have to face a central problem: how to produce a given output at minimum cost when the input prices increase?

The amount of inputs that the firms use will depend on the prices of these inputs. On the short term, the plant size cannot be changed [32]. With a growth of input prices, the firms in a short period may keep the minimum cost by adjusting some input proportions [33]. The silicon price, for example, increases rapidly in recent years, but the price of labor rises very slowly. Firms may reduce the labor and capital inputs to alleviate the impacts of growing material prices. This is termed as the input substitution effect [32,33].

On the long term, the firm adjusts all its inputs such that its cost of production is as low as possible [33]. In the meantime, the firm can change its plant size, design and phase out the old machinery to enhance the efficiency and productivity. Thus the firm keeps the cost of production as low as possible not only by adjusting the input proportions, but also by enhancing the learning effect and expanding the scale of operation to alleviate the impacts of growing material prices. The point is that the firms have a greater flexibility to change its inputs on the long term than on the short term. Perloff [33] indicates that the more time firms have to adjust their inputs, the more factors in production they can change.

Summarizing, on the short term, firms cannot change their plant size and only use the adjustments of input proportions to reduce the impacts of increasing input prices. On the long term, it allows firms to change the plant size and buy new equipment to improve the efficiency and productivity. In the meantime, it also allows the firms to adjust all its inputs to keep the cost of production as low as possible.

3. Methodology

Presently, only a few studies attempt to separate the effects of scale and input prices from the learning effects. Most studies are still using the OFLC to describe cost changes as a result of cumulative output. Nemet [27], however, criticizes that “the learning curve model relies on assumptions about weakly understood empirical studies.” In addition, the linkages between cumulative capacity and technological outcomes are not well understood at this moment. As a result, an alternative approach based on a traditional engineering analysis is adopted by Nemet [27] to analyze technological change. Instead of cumulative output alone, he decomposed the module cost of PV production into several factors: raw material, plant and wafer size, average module cost, and module efficiency, leading to Eq. (5) (Section 1). Nevertheless, 59% of the observed price changes remain unexplained. Pan and Köhler [26] suggested another approach in using a logistic curve to describe the technical changes. They adopt life cycle theory to explain technological changes and integrate the growth rate and R&D investment into the learning curve model to find an expression for the scale of technological change Y_t up to time t:

$$Y_t = \alpha_{lo} + \alpha_{up}\left[1 + \theta \exp\left(-\beta\left(T(1+G) - \frac{\tau}{1+G}\right)\right)\right]^{-1/\theta} \tag{6}$$

in which α_{lo} represents the lower asymptote (saturation level), α_{up} represents the upper asymptote (initial level), β is the average growth rate, θ determines whether the maximum growth occurs early or late, τ represents the time of maximum growth, T is the time period, G is the growth rate of R&D investment. Note that Y_t is also denoted as the degree of maturity for which $\alpha_{lo} < Y_t < \alpha_{up}$. This logistic curve model incorporates all phases of technology development as used in life cycle theory. It also describes the life span of energy technology on the long run. This logistic curve includes the growth rate and R&D investment as the driving variables, however it does not include scale effects and the changes of input prices, as little is known about them.

3.1. The relationships between learning, scale and input prices

In the present research, rather than using the approach of Nemet [27] and Pan and Köhler [26], we follow the approach by Söderholm and Sundqvist [31] and Kahouli-Brahmi [34] to assess the roles of learning-by-doing, learning-by-researching, input prices and scale effects. We will show that using a TFLC is not sufficient to explain cost reduction occurring as a result of learning-by-doing and learning-by-researching: scale effects and input price effects should be incorporated into the learning curve model. The interaction diagram has to be expanded by incorporating the new variables. Fig. 4 presents the linkages and interactions between R&D, learning-by-researching, production

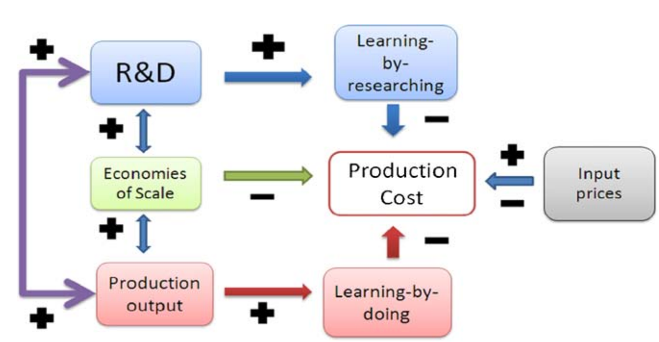

Fig. 4. Relationships and feedbacks between R&D, production growth, economies of scale, prices of input materials and production cost.

outputs, learning-by-doing, economies of scale, input prices, and production cost. This diagram shows that the economies of scale encourage large-scale production, which helps to enhance the R&D investment and promotes learning-by-doing. R&D and production output reduce production cost through enhancing the learning-by-researching rate and learning-by-doing rate. The input prices change the production cost depending on the development of input prices. As the input prices rise (decline), it may increase (decrease) the production cost. However, firms may adjust its input proportions to alleviate the impact of increasing input prices over a short period. In the long run, the learning effect and scale effect help reducing the impacts of increasing input prices [32,33].

3.2. The learning curve model in economic context

Berndt [10] derives the one-factor learning curve from a Cobb-Douglas production function under two assumptions. Söderholm and Sundqvist [31] expand this equation by incorporating the R&D variable to analyze the cost changes of a technology; this was attempted first by Kouvaritakis et al. [35]. Before we develop our model, economic theories involving cost minimization and the Cobb-Douglas CD production function should be introduced and explained briefly.

The theory of cost minimization relies on the assumption that a company chooses inputs to the production process that minimize the total cost of producing output. Usually, two factors are considered, i.e., capital (K) and labor (L), and the third factor, material inputs (M), is ignored [10,30,31]. Yet we, in this study, consider three input elements, labor, capital and materials. As the unit prices of labor (P_L), capital (P_K) and material (P_M) are taken into account, the cost minimization equation can be written as:

$$\text{Minimize}\, C_{total} = P_L \times L + P_K \times K + P_M \times M \tag{7}$$

This equation is then subject to a constraint equation that a fixed output Q_x is to be produced:

$$F(L, K, M) = Q_x \tag{8}$$

where C_{total} represents the total cost of a producing the fixed level of output Q_x.

Perloff [33] indicates that the production function describes the relationship between the amount of inputs used and the maximum quantity of output that can be produced. Here we only introduce the Cobb-Douglas CD function, which normally is defined as:

$$Q_x = AL^{\delta_1} K^{\delta_2} M^{\delta_3} \tag{9}$$

in which δ_1, δ_2 and δ_3 are the elasticity of labor, capital, and materials, respectively ($0 < \delta_1 < 1$, $0 < \delta_2 < 1$ and $0 < \delta_3 < 1$), A represents the technological change element which can be defined as: $A = Q^{-b}KS^{-\alpha}$. In order to solve the minimization or maximization issues, the Lagrangian method is used with function Φ and Lagrange multiplier λ:

$$\Phi = P_L \times L + P_K \times K + P_M \times M - \lambda(AL^{\delta_1} K^{\delta_2} M^{\delta_3} - Q_x) \tag{10}$$

By partial differentiation $\partial\Phi/\partial L = 0$, $\partial\Phi/\partial K = 0$, $\partial\Phi/\partial M = 0$, and $\partial\Phi/\partial\lambda = 0$, we can obtain the following equations:

$$\frac{\partial\Phi}{\partial L} = P_L - \lambda(\delta_1 AL^{\delta_1 - 1} K^{\delta_2} M^{\delta_3}) = 0 \tag{11}$$

$$\frac{\partial\Phi}{\partial K} = P_K - \lambda(\delta_2 L^{\delta_1} K^{\delta_2 - 1} M^{\delta_3}) = 0 \tag{12}$$

$$\frac{\partial\Phi}{\partial M} = P_M - \lambda(\delta_3 AL^{\delta_1} K^{\delta_2} M^{\delta_3 - 1}) = 0 \tag{13}$$

$$\frac{\partial\Phi}{\partial\lambda} = AL^{\delta_1} K^{\delta_2} M^{\delta_3} - Q_x = 0 \tag{14}$$

After some algebraic manipulation and dividing the total cost C divided by the fixed output Q_x, a new model can be obtained [10,30,34]:

$$C_{unit} = aA^{-1/(\delta_1+\delta_2+\delta_3)} Q_x^{(1-(\delta_1+\delta_2+\delta_3))/(\delta_1+\delta_2+\delta_3)} P_L^{\delta_1/(\delta_1+\delta_2+\delta_3)} P_K^{\delta_2/(\delta_1+\delta_2+\delta_3)} P_M^{\delta_3/(\delta_1+\delta_2+\delta_3)} \tag{15}$$

where C_{unit} represents the average unit cost, the parameter a is expressed as

$$a = (\delta_1 + \delta_2 + \delta_3)\,({\delta_1}^{\delta_1} {\delta_2}^{\delta_2} {\delta_3}^{\delta_3})^{-(\delta_1+\delta_2+\delta_3)} \tag{16}$$

and $\delta_1 + \delta_2 + \delta_3$ represents the returns-to-scale parameter (r). After substituting $A = Q^{-b}KS^{-\alpha}$ into Eq. (15), a learning curve, in which the cumulative capacity and R&D are incorporated, is obtained:

$$C_{unit} = aQ^{b/(\delta_1+\delta_2+\delta_3)} KS^{\alpha/(\delta_1+\delta_2+\delta_3)} Q_x^{(1-(\delta_1+\delta_2+\delta_3))/(\delta_1+\delta_2+\delta_3)} P_L^{\delta_1/(\delta_1+\delta_2+\delta_3)} P_K^{\delta_2/(\delta_1+\delta_2+\delta_3)} P_M^{\delta_3/(\delta_1+\delta_2+\delta_3)} \tag{17}$$

Eq. (17) is simplified using the following definitions [30,31]:

$$r = \sum_{i=1}^{n} \delta_i, \quad a = r\left(\prod_{i=1}^{n} {\delta_i}^{\delta_i}\right)^{-1/r},$$

and $P_L^{\delta_1/(\delta_1+\delta_2+\delta_3)} P_K^{\delta_2/(\delta_1+\delta_2+\delta_3)} P_M^{\delta_3/(\delta_1+\delta_2+\delta_3)} = \left(\prod_{i=1}^{n} P_i^{\delta_i}\right)^{1/r}$

This leads to

$$C_{unit} = aQ^{b/r} KS^{\alpha/r} {Q_x}^{(1-r)/r} \left(\prod_{i=1}^{n} P_i^{\delta_i}\right)^{1/r} \tag{18}$$

in which P_i represents the prices of inputs required for producing and operating the technologies, and δ_i is the elasticity of the inputs.

Moreover, there are two assumptions related to this model [2,10,30,31]:

(1) The returns-to-scale parameter is taken constant ($r = 1$). Under this assumption, the term involving the fixed output Q_x, equals 1 and Eq. (18) can be rewritten as:

$$C_{unit} = aQ^b KS^\alpha \prod_{i=1}^{n} P_i^{\delta_i} \tag{19}$$

in which $a = \left(\prod_{i=1}^{n} {\delta_i}^{\delta_i}\right)^{-1}$;

(2) The inflation of input prices is taken into account by using a GDP (gross domestic product) price deflator [36], as it is the most general price index that reflects inflation. The GDP deflator is calculated as the ratio of the value of GDP in current year prices and the value of GDP measured in base-year prices. If we assume that the shares of the inputs in total production costs are identical to the weights used for calculating the GDP price deflator [10,30,31], it implies that $C_{unit} \times \text{GDP price deflator} = aQ^b KS^\alpha \prod_{i=1}^{n} P_i^{\delta}$ and that the GDP price deflator equals $\prod_{i=1}^{n} P_i^{\delta_i}$. The average unit cost C_{unit} is changed to $C_{unit}^{\text{inflation}}$, which thus includes inflation. A simplified learning curve model can be obtained:

$$C_{unit}^{\text{inflation}} = aQ^b KS^\alpha \tag{20}$$

Here, we can see that this equation is similar to the two-factor learning curve. However, the problem is that the scale ($Q_x^{(1-r)/r}$) and input-prices ($\prod_{i=1}^{n} P_i^{\delta_i}$) effect are left out by these two assumptions.

3.3. The multi-factor learning curve model

The theory detailed above can be easily generalized. We observe that when more input prices ($P_1, P_2, P_3, P_4, \ldots$) and learning variables ($q_1, q_2, q_3, q_4, \ldots$) are added to the model, a general form, termed multi-factor learning curve (MFLC), can be obtained:

$$C_{unit} = aQ_x^{(1-r)/r}\left(\prod_{i=1}^{m}(q_i^{\sigma_i})\right)^{1/r}\left(\prod_{i=1}^{n}(P_i^{\delta_i})\right)^{1/r} \tag{21}$$

In this equation, the product $\prod_{i=1}^{m}(q_i^{\sigma_i})^{1/r}$ represents the technological changes, with the σ_i the power of q_i. These are driven by e.g. R&D expenditures (knowledge stock KS), and production expansion (Q), with associated PRs ($PR_{q_i} = 2^{\sigma_i}$), which can be derived from the terms $2^{\sigma_i/r}$. The product $\prod_{i=1}^{n}\left(P_i^{\delta_i}\right)^{\frac{1}{r}}$ represents the impacts of input prices, and $Q_x^{(1-r)/r}$ represents scale effects, which are changed by returns-to-scale. It can reflect the economies and diseconomies of scale effects. Parameters n and m represent the number of considered inputs and learning variables, respectively.

4. Input identification and research boundaries

There are two main types of solar cells in production: crystalline silicon and thin-film cells. Among them, crystalline silicon has the largest share of the market, which is around 90% [19,37,38]. This is expected to be continued for several years at least. Crystalline silicon cells are produced either as single crystal or polycrystalline cells. The single crystal cells are manufactured from silicon crystal ingots. Until recently, most of the materials used for making the silicon cells were left-over from the microelectronics industry. At present, at least nine silicon producers are supplying high-purity silicon to the photovoltaic industry [38].

4.1. Input identification

Swanson [19] indicates that many factors play a role in PV production, but the most important elements are: factory (plant) size, efficiency, silicon, and cell size. Del Cañizo et al. [39] decompose the cost of PV production into several factors: equipment, labor, material, yield losses and a fixed part. Among these inputs, material inputs have the largest share of the total cost, amounting to about 46% while labor accounts for 17%. In a study by Maycock [40], the shares of material and labor cost are around 22–29% and 4–5%, respectively. The basic raw material inputs for producing PV are silicon and silver. Other materials (ethyl-vinyl acetate (EVA), aluminum, other inputs and framing materials) are ignored since they are less costly than silicon and silver [27]. Here we choose plant size being the key factor for the scale effect, and silicon as well as silver being the most essential material inputs.

The silicon price declined from $300/kg in 1975 to $25/kg in 2001 [6]. In recent years, the price has increased to the $40–$50 range for long-term contracts [19]. Subsequently, it has increased to $83/kg in 2006 due to the shortage of silicon [41]. Fig. 5 shows the variation of silicon and silver price over the period 1976–2006. As another important input, the silver price rose from $4.3/ounce in 1976 to $20/ounce in 1980 due to the severe shortage of silver supply [42]. It fell sharply from $20/ounce to $7/ounce within 2 years. Subsequently, the silver price fluctuated between $6/ounce to $4/ounce. With the strong growth of the gold price, silver price has increased to $11/ounce recently.

In the 1970s and 1980s, the average plant size of PV cell manufacturing was around 1 MW [43]. Maycock [44] indicated that Kyocera, the second largest producer of PV module in Japan, had expanded its capacity to 2 MW in 1993. It planned to expand its plant size to 4 MW in the next few years. In recent years, Mitsubishi Electric expanded its plant size from 24 MW in 2002 to 35 MW in 2003 and increased to 50 MW in 2004 [45]. For 2007 it is reported that the Japanese company Sanyo stated that they had 165 MW of capacity, and plans to increase its plant size to 350 MW in 2008 [46]. We thus construct the historical development of plant size as presented in Fig. 6.

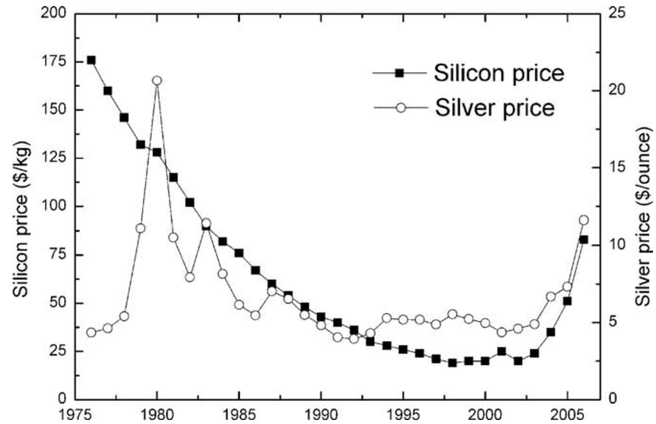

Fig. 5. Development of silicon and silver prices, 1976–2006.*Source*: (1) Silicon prices: [43,45], (2) silver prices: [42].

4.2. Research boundary and the MFLC model for PV production cost

Although many economic studies have been performed on labor, capital and other materials cost, little is known about the historical data of these factors in PV production. In addition, little R&D data can be obtained from the PV companies as well, due to confidentially issues. Thus learning-by-researching, labor and capital are omitted in this study, but these factors will be included by introducing a remaining-factors term, see below. For the inputs, only silicon and silver are chosen to be the input factors. The other material inputs (glass, aluminum, etc.) are grouped into one 'other' factor (O). The cost minimization equation then is rewritten as:

$$\text{Minimize}\, C_{total} = P_{\mathrm{Si}}\mathrm{Si} + P_{\mathrm{Ag}}\mathrm{Ag} + P_{\mathrm{O}}\mathrm{O} \tag{22}$$

in which P_{Si}, P_{Ag} and P_{O} represent the unit prices of silicon (Si), silver (Ag) and other inputs (O), respectively. The Cobb-Douglas function has to be rewritten by adding these inputs:

$$Q_x = A\mathrm{Si}^{\delta_3}\mathrm{Ag}^{\delta_4}\mathrm{O}^{\delta_5} \tag{23}$$

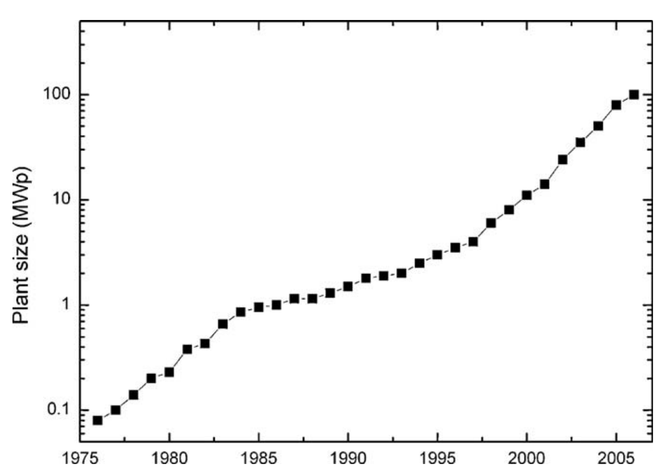

Fig. 6. PV plant size (MW) from 1976 to 2006.*Source*: [43,45].

where δ_3, δ_4, and δ_5 are the elasticity of silicon, silver and other inputs, respectively.

After identifying the main factors, the cost minimization equation (Eq. (22)) is subjected to the Cobb-Douglas function (Eq. (23)). Then by using the method of Lagrange multiplier, Eq. (10) is rewritten to yield:

$$\Phi = P_{Si} \times Si + P_{Ag} \times Ag + P_O \times O - \lambda(ASi^{\delta_3} Ag^{\delta_4} O^{\delta_5} - Q_x) \quad (24)$$

After partial differentiation $\partial\Phi/\partial\,Si = 0$, $\partial\,\Phi/\partial\,Ag = 0$, $\partial\,\Phi/\partial\,O = 0$, and $\partial\,\Phi/\partial\,\lambda = 0$ and dividing the total cost C_{total} by the fixed output Q_x, we can obtain the following multi-factor learning curve model:

$$C_{unit} = aQ^{b/r} Q_x^{(1-r)/r} (P_{Si}^{\delta_3} P_{Ag}^{\delta_4} P_O^{\delta_5})^{1/r} \quad (25)$$

in which $r = \delta_3 + \delta_4 + \delta_5$ is the returns-to-scale parameter, and $a = r(\delta_3^{\delta_3} \delta_4^{\delta_4} \delta_5^{\delta_5})^{-1/r}$ is a constant term.

By taking the logarithm on both sides of Eq. (25), a linear form is obtained:

$$\log C_{unit} = \log a + b_1 \log Q + n \log Q_x + \delta_{Si} \log P_{Si} + \delta_{Ag} \log P_{Ag} + \delta_O \log P_O \quad (26)$$

in which the coefficients are defined as:

$\log a$	Remaining-factors effect
$b_1 = b(n+1)$	Learning-by-doing index
$\alpha_1 = \alpha(n+1)$	Learning-by-researching index
$n = (1-r)/r$	Scale index or the elasticity of plant size
$\delta_{Si} = \delta_3\ (n+1)$	Silicon price index
$\delta_{Ag} = \delta_4\ (n+1)$	Silver price index
$\delta_O = \delta_5\ (n+1)$	Other input-prices index

It is clear that Eq. (26) decomposes the unit cost of PV production into four major parts: learning-by-doing, scale, input-prices and remaining-factors effect:

(1) *Learning-by-doing*: It is represented by the term $b_1 \log Q$. The coefficient b_1 is determined by the scale index n, which reflects that leaning-by-doing is enhanced as the economies of scale are taking place ($r > 1$).
(2) *Scale effect*: The scale effects are reflected by the term $n \log Q_x$. The returns-to-scale, in the model, does not only affect the scale index, but also changes the elasticity of learning and input prices. However, by setting returns-to-scale constant ($r = 1$), the scale effect can be omitted from the model.
(3) *Input-price effect*: The rest of Eq. (26) ($\delta_{Si} \log P_{Si} + \delta_{Ag} \log P_{Ag} + \delta_O \log P_O$) reflects all changes due to input prices. The input prices are mainly changed by the elasticity of the inputs and the returns-to-scale. The substitution effect also occurs between these input factors. The term $\delta_O \log P_O$ represents the other input-prices effect. Since actual data of other inputs cannot be obtained, this part is calculated by $\delta_O \log P_O = \log C_{unit} - (\log a + b_1 \log Q + n \log Q_x + \delta_{Si} \log P_{Si} + \delta_{Ag} \log P_{Ag})$. It can be regarded as the residual term in this research.
(4) *Remaining-factors effect*: $\log a$ is the constant term in the MFLC model which shows that when all the independent variables ($b_1 \log Q$, $n \log Q_x$, etc.) in this model equal to zero, $\log a$ equals to $\log C_{unit}$. It infers that not only are the costs determined by learning-by-doing, scale and input-prices, but also by other factors (such as learning-by-searching, subsidies, labor, etc.). In this study, $\log a$ represents the remaining-factors effect, which reflects two types of factors: first, the factors have been incorporated in this model, but left out from this study due to lack of the historical data (such as labor, capital and R&D); second, the factors have not been discussed in this study (such as subsidies, taxes and O&M cost). Thus these factors are grouped into the constant term $\log a$. In a further study, these factors should be incorporated into the research.

To summarize, the MFLC decomposes the cost into three major effects: learning-by-doing, scale and input price effect. The elasticity or indexes of the learning, scale and input prices are shaped by the return-to-scales. The remaining-factors effect represents the effects that are out of this research scope for various reasons discussed above. Other material inputs are grouped into one factor $\delta_O \log P_O$, which can be regarded as the residual term.

5. Results and residuals

In the following paragraphs, results of the simulations are presented. The numbers and figures acquired by running the MFLC model are interpreted by using the concepts described above. In order to demonstrate the impacts of these effects on cost reduction, the analysis and discussion is divided into three parts. In the first part (Section 5.1), regression is carried out to obtain the values of the variables discussed above. In the second part (Section 5.2), the results are investigated by dividing the learning curve into three time periods: (1) 1976–1986, (2) 1987–1997, and (3) 1998–2006. Uncertainty and sensitivity issues are discussed in the last part, Section 5.3.

5.1. Parameters and statistical analysis

The values of the variables from Eq. (26) are determined by using multivariate regression [9]; here we used the regression function available in Microsoft Excel on the data presented in Fig. 2 and Section 4.1. The base of the log numbers is 10. The results of the regression are listed in Table 3; the fit to the data is shown in Fig. 7, and compared to the OFLC fit.

For the complete data period 1976–2006, the scale index (n) is -0.062, which is less than -0.07 [47] and -0.09 [48] (see Table 2). Compared with the OFLC model, the learning rate of this study is 13.5% (inferred from parameter b_1 and Eq. (3)), which is lower than the OFLC one (19.5%). The positive index of silicon-price implies that the effect of silicon increases with a rise of the silicon price. The negative index of silver-price indicates that the effect of silver is contrary to that of the silicon price. The larger returns-to-scale ($r > 1$) obtained from $n = (1-r)/r$ is 1.07, which shows that economies of scale takes place in this simulation. The δ_O computed by this model is 0.853. Fig. 7 shows two fits, one with and one without the other input effects included; there are only slight differences. Of the coefficients, the standard errors of n and δ_{Ag} are 49% and 35%, respectively. This indicates that there are some uncertainties, which may exist in the historical data. One of the uncertainties for the plant size might result from the various expansion rates among countries. Both silver and silicon, but also the PV unit prices, are average prices for each year, which may bring some averaging uncertainties to this model.

Table 3
The values of the variables.

Parameter	Value	Standard error
$\log a$	1.058	0.112
b_1	−0.210	0.028
n	−0.062	0.030
δ_{Si}	0.285	0.050
δ_{Ag}	−0.138	0.048
δ_O	0.853	0.031

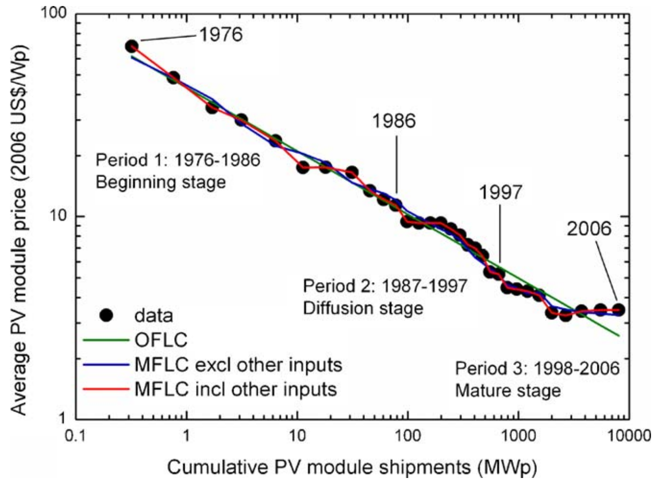

Fig. 7. The PV learning curve fitted to the OFLC and MFLC model (with and without including other input effects) for the period 1976–2006.

A measure of the goodness of the fit to the experimental data is the coefficient of determination, R^2. A value of R^2 close to one usually shows an excellent overall fit, while a value near zero shows a failure of the estimated regression. The R^2 of the regression yielding the parameter values as given in Table 3 is 0.993, which shows that the estimated regression equation fits the historical data quite well. Compared with the OFLC, the R^2 of the MFLC is better than that of the OFLC, whose R^2 is 0.9828. Moreover, performing a Student t-test, it was found that the Student t-values all are well above 1.96 (5% statistical significance level), which implies that the values of the coefficients are statistically significant. We therefore confidently will use the set of coefficients shown in Table 3 in the following simulations.

5.2. The results of the multi-factor learning curve

In order to forecast future prices of PV modules, historical simulation is of great importance. The regression results on the above parameters were used to obtain the effects of remaining-factors learning-by-doing, scale and input-prices. The final results of these effects are shown in Fig. 8, with data in Tables 4–6, and have been determined using the following equation:

$$C_{unit} = \frac{C_{unit}}{\log C_{unit}}(\log a + b_1 \log Q + n \log Q_x + \delta_{\mathrm{Si}} \log P_{\mathrm{Si}} + \delta_{\mathrm{Ag}} \log P_{\mathrm{Ag}} + \delta_{\mathrm{O}} \log P_{\mathrm{O}}) \quad (27)$$

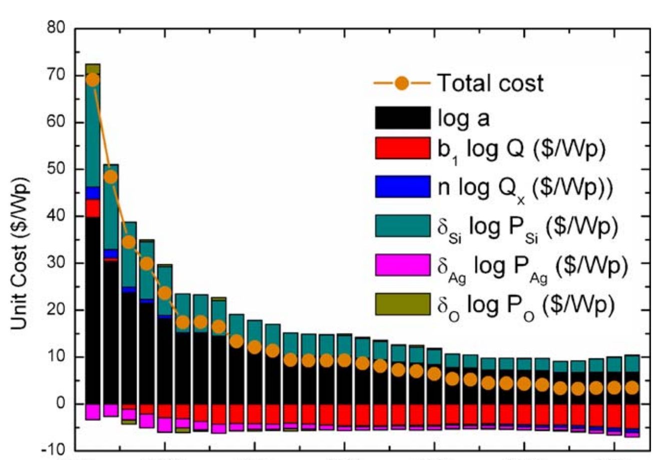

Fig. 8. Breakdown of factors contributing to the unit cost.

Table 4
Summary of the MFLC results for time period, 1976–1986.

Factor	Change	Effects on MFLC module cost in 2006 price ($/Wp)	OFLC ($/Wp)
Remaining-factors		−28.371	
Learning	0.32–77.78 MWp	−8.170	−50.67
Scale effect (plant size)	0.08–1 MW	−2.545	
Silicon price	$176/kg–$67/kg	−18.470	
Silver price	$4.35/ounce–$5.46/ounce	2.216	
Sum of factors		−55.341	−50.67
Others inputs (residual)		−2.404	−7.075
Actual change		−57.745	−57.745

Table 5
Summary of the MFLC results for time period, 1987–1997.

Factor	Change	Effects on MFLC module cost in 2006 price ($/Wp)	OFLC ($/Wp)
Remaining-factors		−2.548	
Learning	98–662.53 MWp	−0.256	−4.620
Scale effect (plant size)	1.15–4 MW	−0.234	
Silicon price	$60/kg–$21/kg	−2.169	
Silver price	$7/ounce–$4.87/ounce	0.441	
Sum of factors		−4.767	−4.620
Others inputs (residual)		0.550	0.403
Actual change		−4.217	−4.217

The overall effects were presented in Fig. 7. Note that of these effects, learning-by-doing, remaining-factors and silicon-price effect contribute the most to the cost reduction of PV. Here it will be helpful to realize the interactions between these factors by dividing the results into three time periods: (1) 1976–1986 (the beginning stage); (2) 1987–1997 (the diffusion stage); (3) 1998–2006 (the mature stage). We choose these periods for three reasons. First, since most technologies just emerged from the laboratory over the first period, the cumulative output was quite low. The learning-by-doing effect plays a minor role in this period. No economies of scale took place over this period. Second, the market had already shifted from space satellite applications to terrestrial ones. The economies of scale came in, but less important. The learning-by-doing effect still played a minor role in cost reduction at the second stage. Third, scale effect became

Table 6
Summary of the MFLC results for time period, 1998–2006.

Factor	Change	Effects on MFLC module cost in 2006 price ($/Wp)	OFLC ($/Wp)
Remaining-factors		−0.481	
Learning	793.5–8070 MWp	−1.081	−2.764
Scale effect (plant size)	6–100 MW	−0.463	
Silicon price	$19/kg–$83/kg	1.008	
Silver price	$5/ounce–$11.62/ounce	−0.239	
Sum of factors		−1.257	−2.764
Others inputs (residual)		0.252	1.759
Actual change		−1.005	−1.005

significant in the third period. The learning-by-doing effect played a key role in this period. In the following paragraphs, the differences in the factors and residual in these three periods are depicted by comparing with OFLC model.

5.2.1. Period 1976–1986

The PV market was still at the beginning stage. The actual price of a PV module fell from \$69/Wp in 1976 to \$11/Wp in 1986. The outputs and plant sizes were very small. Space satellite applications dominated market growth in this period [6,19]. Three factors, i.e., remaining-factors, silicon price and learning, accounted for the largest changes in cost. The factors scale and other inputs were of less importance but played a role in this period.

Remaining-factors effect: Of the factors we identify, the declining remaining-factors accounted for the largest changes (~49%) in cost (see Fig. 8 and Table 4). At this stage, most technologies just emerged from the laboratory and tended to promote themselves on the market before being commercialized. The public R&D and governmental subsidies meanwhile helped the PV industry shifting from the invention to the diffusion stage [27]. In the mid-1970s, the birth of the terrestrial PV industry shifted the market away from space applications [6,19]. Thus it is important to note that the early development of PV production only focused on research and innovation. Learning-by-researching was of much importance during this period. It might be the major factor to account for the falling of remaining-factors effect at this stage.

Learning effect: The learning effect during the first 2 years (see Fig. 8) did not play a role to give a positive impact on cost reduction since many technologies just emerged from the laboratory. Subsequently, the learning effect came in to decrease the PV module price, but it was not so important. It only accounted for 13.6% of the total reduction over this period.

Silicon-price effect: Silicon prices, at this stage, decreased from \$176/kg in 1976 to \$67/kg in 1986, but still stood at a high level. It contributed to the cost reduction by 32%.

Silver-price effect: The silver price first increased rapidly to \$20/ounce within 4 years. During this period, for decreasing the production cost, firms adjusted their input proportions by shifting away from silver to use other materials, known as the input substitution effect [32,33]. After that, the price declined to the normal level, around \$5/ounce–\$7/ounce range. Firms preferred to use more silver for producing PV modules. It explains the cost being increased by the silver-price effect.

Scale effect: All plants in this period were smaller than 1 MW. The scale effects were not significant over this period. It only accounted for 4.6% of the total reduction. Thus the scale index (n) could be assumed as zero and the returns-to-scale would be constant ($r = 1$). The model could therefore be simplified as:

$$\log C_{unit} = \log a + b \log Q + \delta_3 \log P_{Si} + \delta_4 \log P_{Ag} + \delta_5 \log P_O \quad (28)$$

This equation describes that the cost changes of PV in this period were only dominated by remaining-factors ($\log a$), learning effect ($b \log Q$) and input-prices: silicon and silver.

Compared with the OFLC model over this period, the residual (other inputs) of the MFLC model in this period only accounted for 4.2%, which is smaller than the OFLC one (12.3%). These five factors of the MFLC model together explained more than 96% of the change in cost over this period, but OFLC only explained 88% of the total change in cost.

5.2.2. Period 1987–1997

In this period, the costs of PV production slightly went up, but the tendency still was to go down. The PV module price decreased by 45%, from \$9.4/Wp in 1987 to \$5.2/Wp in 1997. The PV market had turned to the diffusion stage. The cumulative output and plant size increased steadily. Among these factors, remaining-factors and silicon price contributed the most to cost reduction (see Fig. 8 and Table 5). Other factors still played a role at this stage, but less important.

Remaining-factors effect: Compared to the first period, the decreasing rate of remaining-factors fell to 2.7% per year, but it still dominated the cost reduction. Compared to the period of 1976–1986, the large decreases not only resulted from learning-by-researching, but also from governmental subsidies [27]. Japan launched a set of programs for supporting its PV industry since the early 1970s [49]. Germany in 1991 introduced the feed-in law to enlarge the renewable energy market [50]. USA and other countries meanwhile had the same subsidy programs. It was clear that the governmental subsides contributed the most to the falling of remaining-factors effect over this period.

Learning effect: At this stage, the learning effect only contributes a little (6%) for cost reduction. The cumulative output of PV modules slightly increased from 98 MWp 1987 to 662.53 MWp. This increase could not bring out a significant impact on PV cost reduction.

Scale effect: Unlike the first period, the scale effect in this period started to become important to give a positive impact on cost reduction. The plant size was expanded from 1 MW to 4 MW. However, it was too small to give a significant impact on cost reduction, but it still played a role over this period.

Silicon-price effect: The prices of silicon declined by 65% in this period that resulted in cost falling as well. Its contribution accounted for 50% of the total reduction.

Silver-price effect: The silver price at this stage decreased by 30%. Firms increased the use of silver instead of other expensive materials. That might be one of the reasons that the cost of PV production increased somewhat. Another reason is the effects of other input-prices (see Fig. 8). In this period, the increase in capital and labor to expand the plant size may result in the effects of other input-prices rising a little in the period of 1990–1995.

5.2.3. Period 1998–2006

In this period, the PV production had already shifted from diffusion stage to mature stage. Fig. 2 shows that the curve became flat over 2002–2006 and the cost of PV production stopped falling. The price of PV modules was slightly decreased by 22%. Compared to the first two periods, of these factors, learning effect, scale effect and remaining-factors contributed the most to cost reduction. Silicon-price effect, in contrast to the past, played a different role in this period. As we observed earlier capacity shortages among solar cell and module manufacturers are likely to be partially responsible for the increase in module prices after 2002, but it is very difficult to quantify this effect. The quick expansion of the PV market after 2002 led also to steep increases in the price of high-purity silicon. If we analyze this period under the assumption that the market price did nonetheless reflect production cost we may observe that compared to the first two periods, the contribution of learning effect, scale effect and remaining-factors contributed the most to cost reduction. The silicon-price effect, in contrast to the past, played a different role in this period.

Learning effect: Only looking at the OFLC figure, we might simply infer that no learning effect is taking place at this stage. The fact, however, was that the learning effects obtained by running the MFLC model were still present as in the other periods. The decreasing rate of learning effect over this period was around 3% per year. It accounted for the largest part of cost reduction at this stage (see Table 6 and Fig. 8).

Scale effect: Aside from learning effect, the scale effect is of large importance due to the rapid expansion of plant size from 6 MW in 1998 to around 100 MW in 2006. The decreasing rate of scale effects was 11.6% per year. The economies of scale played a significant role in this period. With the expansion of plan size in the

future, the contribution of scale effect will be much more important than the past.

Silicon-price effect: The silicon prices in this period boosted quickly from $24/kg in 1998 to $83/kg in 2006 due to shortage of silicon. Until now, the spot market price even is over $300/kg. Consequently, it caused the rise of production cost. Table 6 shows that the increased silicon-price effect almost neutralized the decreased learning effect.

Silver-price effect: As the Silver Institute [42] mentioned, the silver price increased by 110%, up to $11/ounce in 2006. This caused the firms adjusting the proportions of input materials to avoid the lost. As a result, decreasing the use of silver leads to a reduction in the cost of PV production.

Remaining-factors effect: The effect of remaining-factors, at this stage, became smaller. It played a role in cost reduction, but of less importance than before.

Overall, in this period only the silicon effect gave a negative impact on cost reduction. It lead to an increase of the cost of PV production. The rest of the effects, learning, scale, remaining-factors and silver-price effects, still gave a positive impact on cost reduction leading to a reduction of the cost of PV production, but these effects were counteracted by the increase of the silicon effect (learning effect + scale effect + remaining-factors effect + silver effect–silicon effect). The overall effects in this period were much smaller than in earlier periods. As a result, it caused the PV module price to decrease slightly. The MFLC shows that the rising silicon price weakened the learning effect. The module price stopped falling, while the cumulative output still increased.

To summarize, through the above investigation, we demonstrate that the cost reduction of PV production actually is explained by a set of effects, rather than by learning-by-doing alone. Once the expansion of plant size and the growth of input prices take place to change the cost of PV production over a short period, the OFLC model cannot reflect these effects and gives us a wrong impression, i.e., no learning effect is taking place over this time period. It certainly causes one major issue, that in the long-term forecasting the estimations of the OFLC are less reliable due to lack of scale, input-prices and other effects. Furthermore, in this historical analysis, we find that the assumption of the shares of the inputs in total production costs being identical to the weights used for calculating the GDP price deflator in order to leave out the input-prices effect is a very weak hypothesis. The silicon-price effect, for example, in this study does play an important role over the period of 1976–2006, especially in recent years. It cannot be omitted from the model.

5.3. Sensitivity and uncertainty

In this section uncertainty in four factors is addressed: cumulative output, plant size, silicon price and silver price. The sensitivity of the model is tested by considering an increase and a decrease of 80% in each of the four factors. The model is most sensitive to uncertainty in two variables: cumulative output and silicon price, which is indicated in Fig. 9. The plant size is of moderate importance at this moment. If the plant size will continue to increase, the scale effect will become much more significant. Since the standard error for plant size index and silver-price index are relatively high, 49% and 35%, respectively (see Table 3), it indicates that there are some uncertainties existing in the historical data. The sensitivity analysis here for plant size and silver price therefore is less reliable.

With converting the learning curve into linear form (logarithm), the stochastic error term or residual term must be present in a regression equation, since the real-world costs are not exactly the same as the estimated costs. The residuals represented by $\delta_5 \log P_O$ in the MFLC model may result from three sources: (1) other minor influences on estimation of cost that are omitted from the equation (such as the input of glass); (2) cross-countries data are not easily obtained and in some cases, having the data is impossible. Since the labor cost, investment and O&M may easily vary among countries, global data for these factors does not exist. For example, the labor cost in China is much lower than that in Japan. In addition, the prices of silicon and plant size (1976–2001) are acquired from the figures of Nemet's study [43]. Since the expansion rates of the plant size are different among the countries, finding the global data is not easy. These may enlarge the uncertainties of the results; (3) all attempts to generalize human behavior must contain at least some amount of unpredictable variation.

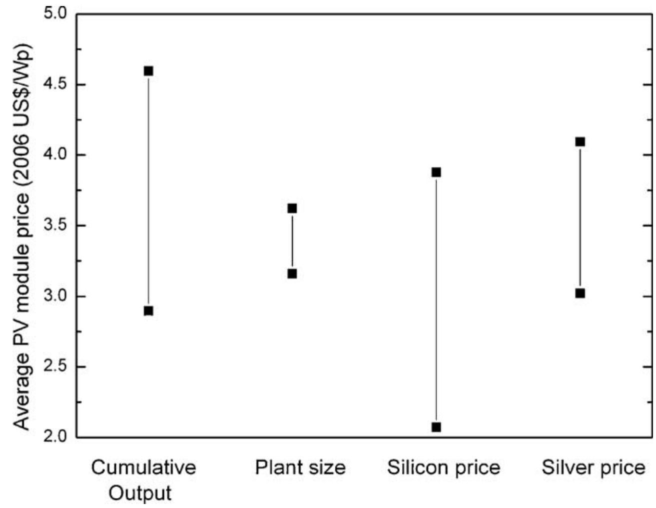

Fig. 9. Sensitivity of the MFLC model to a variation of four factors.

6. A MFLC forecast for future PV cost

Having now available a fit to the historical data, in which the influence of several factors now is clear, it is possible to forecast PV cost development, based on expert data or opinion. For example, forecasts of silicon price can be used in combination with plant size developments. In this section we briefly explore two scenarios, as an illustration how the MFLC could be used in a more reliable prediction of future cost than the OFLC.

Like many studies of future PV cost estimations, Van der Zwaan and Rabl [51] apply a progress ratio of 0.80 to estimate that the cumulative PV production has to be increased to 148 GW in order to reach a break-even cost of $1/Wp. The current cumulative production is about 8070 MWp [45]. Maycock [52] predicts that the world PV module production will increase from 955 MW/year in 2004 to 4000 MW/year in 2010. The unit cost will reach $2/W. Swanson [19] forecasts that assuming the growth of the market at 30% per year, a price of $1.56/W is obtained in 2012. However, all these estimations are based on the OFLC model and ignore the rising input-prices effect and economies of scale effect. For a better understanding of the interactions between these factors in our MFLC model, two short term scenarios with various silicon prices are carried out, scenario MFLC-1 and MFLC-2.

Before turning to the simulation, the input data of this scenario have to be set up. Rogol [41] makes a forecast on PV future development over the time period of 2007–2011. First of all, he believes that with the growth of the new suppliers in China, more silicon supply will come on line than was estimated before. He also estimates the average of both indirect and direct sales, to be $103/kg in 2007 and $109/kg in 2008, but the price will drop to $97/kg in

Table 7
The data are used in scenario MFLC-1, 2007–2011.

Year	Cumulative capacity (MWp)	Plant size (MW)	Silicon price ($/kg)	Silver price ($/ounce)
2007	12,070	165	103	13.39
2008	18,370	350	109	17.52
2009	29,270	500	106	14.5
2010	46,470	600	101	13.1
2011	69,170	875	97	13.0

2011. With more silicon production, Rogol [41] also foresees that the world production of PV module will increase to 4 GW in 2007, 6.3 GW in 2008, 10.9 MW in 2009, 17.2 MW in 2010, and 22.7 GW in 2011.

At the same time, the Japanese company Sanyo stated that they had 165 MW of capacity in 2007, and plans to increase its plant size to 350 MW in 2008 [45]. Trina, a Chinese company, claims that they had 150 MW of capacity in 2008 and will expand to 350 MW in 2008 as well. Both Solland and EverQ plan to raise their capacity to 600 MW by 2010. E-Ton is aiming at building a 500 MW plant in 2009. Sunpower declares that they plan to expand its plant to 875 MW in 2011.

The Silver Institute [42] points out that the silver price increases from $4.6/ounce in 2002 to $13.39/ounce in 2007 and the current average price is around $17.52/ounce (May 2008). The average rate of increase between 2002 and 2008 is 24.97%. For the future, Klapwijk [53] predicts that silver price will fall to the $13/ounce–$16/ounce range. Thus this study assumes the future price will decrease to $13/ounce in 2011. The average decreasing rate between 2009 and 2011 will be around 9.46%.

All data used for a short-term scenario are listed in Table 7. This scenario is referred to as scenario MFLC-1.

6.1. Short-term scenario MFLC-1

The results of this scenario compared with the OFLC model are shown in Table 8. In the period of 2007–2011, the PV production has already shifted to a mature stage. The expansion of the PV market is still ongoing. The plant size will increase to over 800 MW. The world cumulative output of PV production will rise to 69 GW in 2011. The scenario shows that learning and scale effect will account for most of the reduction in cost. Other factors will play a role in this period, but less important.

Learning effect: In this period, the cumulative output increases rapidly. The improvement of the production process and labor efficiency, the introduction of new equipment and production methods, and the changes in the organization enhance the learning rate. All these lead to the fact that the learning effect contributes the most to cost reduction.

Scale effect: With the increases of plant size, the scale effect is of much more significance in this period than the past. The economies of scale, at this stage, ensure the firms to gain the benefits from the larger specialization of workers and managers. In addition, it also helps to enhance the learning-by-doing rate. In the future, its role in cost reduction will be of importance.

Silicon-price effect: Rogol [41] predicts that the silicon price will first increase to $109/kg due to shortage of silicon, but, with more silicon suppliers in China, the price will decrease to $97/kg. Comparing this with the past, it still stands at a high level. In contrast to the learning and scale effect, the silicon-price effect increases the cost, thus yielding a negative impact on cost reduction.

Silver-price effect: Silver-price effect in this period still plays a minor role since silver prices are relatively stable. It allows the firms to adjust the proportions of input materials slightly to overcome the impact of silver-price effect.

Remaining-factors effect: The remaining-factors effect plays an entirely different role in this period, it slightly increases by 9% in 2011. Together with the silicon-price effect, it increases the cost of PV production to give a negative impact on cost reduction.

Overall, the expansion of plant size leads to the fact that the economies of scale are becoming much more important than before. Economies of scale enhance the learning-by-doing effect. Silver-price effect meanwhile plays a role, but less important. The high prices of silicon as well as remaining-factors effect, however, increase the cost of production to give a negative impact on cost reduction, thus weakening the cost decreases due to the learning and scale effect. As a result, the overall effect is an upward shift of the average cost curve. The multi-factor learning curve can reflect all these effects sufficiently. Thus the price of PV modules will decrease from $3.047/Wp in 2007 to $1.881/Wp in 2011. Fig. 10 shows that the prices forecasted by the MFLC will not follow the OFLC trajectory anymore, but are shifted upwards.

Table 8
Summary of the MFLC-1 scenario results for time period, 2007–2011.

Factor	Change	Effects on MFLC module cost in 2006 price ($/Wp)	OFLC
($/Wp)			
Remaining-factors		0.592	
Learning	12–69GW	−1.570	−0.963
Scale effect (plant size)	165–875 MW	−0.383	
Silicon price	$103/kg–$97/kg	0.270	
Silver price	$13.39/ounce–$13/ounce	−0.075	
Sum of factors		−1.166	−0.963

6.2. Short-term scenario with lower silicon prices in 2010 and 2011 (MFLC-2)

Since Swanson [19] mentions that the price recently has increased to the $40–$50 range for long-term contracts, Rogol [41]

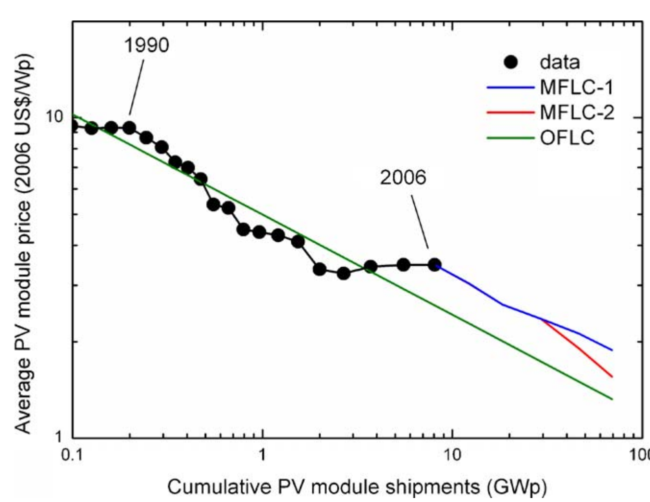

Fig. 10. The PV learning curve extrapolated to 2011 using the MFLC model for two scenarios, MFLC-1 and MFLC-2, compared to the OFLC.

might overestimate the future silicon prices. In an alternative second scenario (MFLC-2), we assume that the silicon price may decrease from \$106/kg in 2009 to \$70/kg in 2010 and to \$50/kg in 2011, while all other data as stated in Table 7 remain the same.

Fig. 10 shows the effect on the learning curve. Of the effects, only the silicon-price effect decreases slightly due to the assumed decreases of silicon prices in 2010 and 2011, but together with the remaining-factors effect, it still gives a negative impact on cost reduction. The learning-by-doing and scale effect still play the key roles in cost reduction over this period. Silver-price effect plays a role as above, but less important.

The overall result on the learning curve using this lower silicon price scenario is shown in Fig. 10 (MFLC-2). Since the silicon prices decrease from \$106/kg in 2009 to \$70/kg in 2010 and to \$50/kg in 2011, the silicon effect falls which leads the cost of PV production to decrease from \$3.047/Wp in 2007 to \$1.556/Wp in 2011. The learning-by-doing and scale effect still play the key roles in cost reduction over this period. Silver-price effect plays a role as above, but less important. Compared to the prices in 2010 and 2011 for the first scenario MFLC-1, the price of PV module reduces by \$0.21 in 2010 and \$0.244 in 2011. It proves that the input-prices play an important role in cost reduction. Compared with the OFLC, the MFLC model reflects the changes of silicon prices, which lead to the falling of cost in 2010 and 2011.

7. Conclusion

This study was motivated by the fact that the one factor learning curve ignores some factors and uncertainties, which are vital in driving cost reduction. As recent cost data evidences, the market price of PV modules stabilizes as the cumulative output increases, which would imply that no technological improvement takes place in these periods. In order to address this issue, the paper has described a methodology, named the multi-factor learning curve, to incorporate the scale and input-prices effect as the additional variables into the one factor learning curve. The multi-factor learning curve is not only derived from the economic theories, but also supported by an empirical study, for the case of PV technology development.

The results of this research challenge the credibility of the one factor learning curve. They confirm that a learning curve actually represents a combined effect on cost reduction, rather than learning by doing alone. At the technology emerging stage, the learning effect plays a minor role in cost reduction. No economies of scale take place at this stage. The factors that drive the cost decline in case of PV technology development are silicon price and other factors (such as learning-by-researching, subsidies from government). At the diffusion stage, the economies of scale effect starts to play a role in cost reduction, but it is not so important. The learning effect also accounts only to a small extent to cost reduction. The other factors and input-prices effect still play an important role in cost reduction at this stage. At the mature stage, learning and scale effect instead of input prices and other factors contribute the most to cost reduction.

We have shown that the one factor learning curve may successfully describe the cost reduction at the technology emerging stage, but fails to explain the changes in cost at the mature stage. The OFLC cannot reflect the cost changes caused by the growth of input-prices. As a consequence, the costs estimated by the OFLC are lower than the market ones. The MFLC reflects all these changes sufficiently to present a reliable result for cost reduction.

In addition, the results also verify the assertion by Isoard and Soria [30], and Pindyck and Rubinfeld [32] that economies of scale play an important role in a large scale production due to the larger scale of a production plant allowing managers and workers to have a larger specialization in their tasks. We also find that the assumption about the shares of the inputs in total production costs being identical to the weights used for calculating the GDP price deflator is a weak hypothesis. Our results reveal that the silicon-price effect does play an essential role in cost changes. The input-prices effect should not be eliminated from the model.

Compared with the one factor learning curve, the MFLC model solves the discontinuity issue, which exists in the one factor learning curve. Furthermore, the MFLC model has a better capability than the OFLC in forecasting future cost since the cost production is not only determined by cumulative output alone, but also by scale, input-prices and other factors. As a result, the reliability of the estimated costs has been improved by the MFLC model. The MFLC model, in addition, is not only restricted for use in the PV technology case study, but it can easily be used for other technologies (such as wind power and biomass), e.g. data on steel price development could help to elucidate wind turbine cost development.

However, some issues related to the research still remain unsolved. First, since many factors such as labor, investment and learning-by-researching are omitted from this study, the effects of remaining-factors contributing to the cost reduction are not very clear. In addition, this model cannot tackle the issue of lack of representation of institutional structures (such as subsidies). In future studies, we recommend two issues to be investigated: the first issue is that some factors which have been incorporated in to the MFLC model are left out from this study due to the absence of historical data (such as labor, capital, and learning-by-researching). Thus, seeking reliable historical data is required. The second issue is that some factors that are not discussed in this study should be investigated as to how to incorporate them into the MFLC model. For example, the effect of feed-in law should be investigated to incorporate into this model.

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